Model distillation and extraction

CS 685, Spring 2022

Advanced Natural Language Processing

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many slides from Kalpesh Krishna

stuff from last time…

- Exam grading hopefully done by Sunday evening, regrades will be on for one week
    - note that scores can go *down* as well if you submit a regrade request
- Homework 2 due May 4th
- Final project reports due May 12, 11:59pm
    - Report PDF due on Gradescope, code via email to instructors account with README
        - Email with either **public** GitHub link or zip file is fine

Knowledge distillation:

A small model (the **student**) is trained to mimic the predictions of a much larger pretrained model (the **teacher**)

Bucila et al., 2006; Hinton et al., 2015

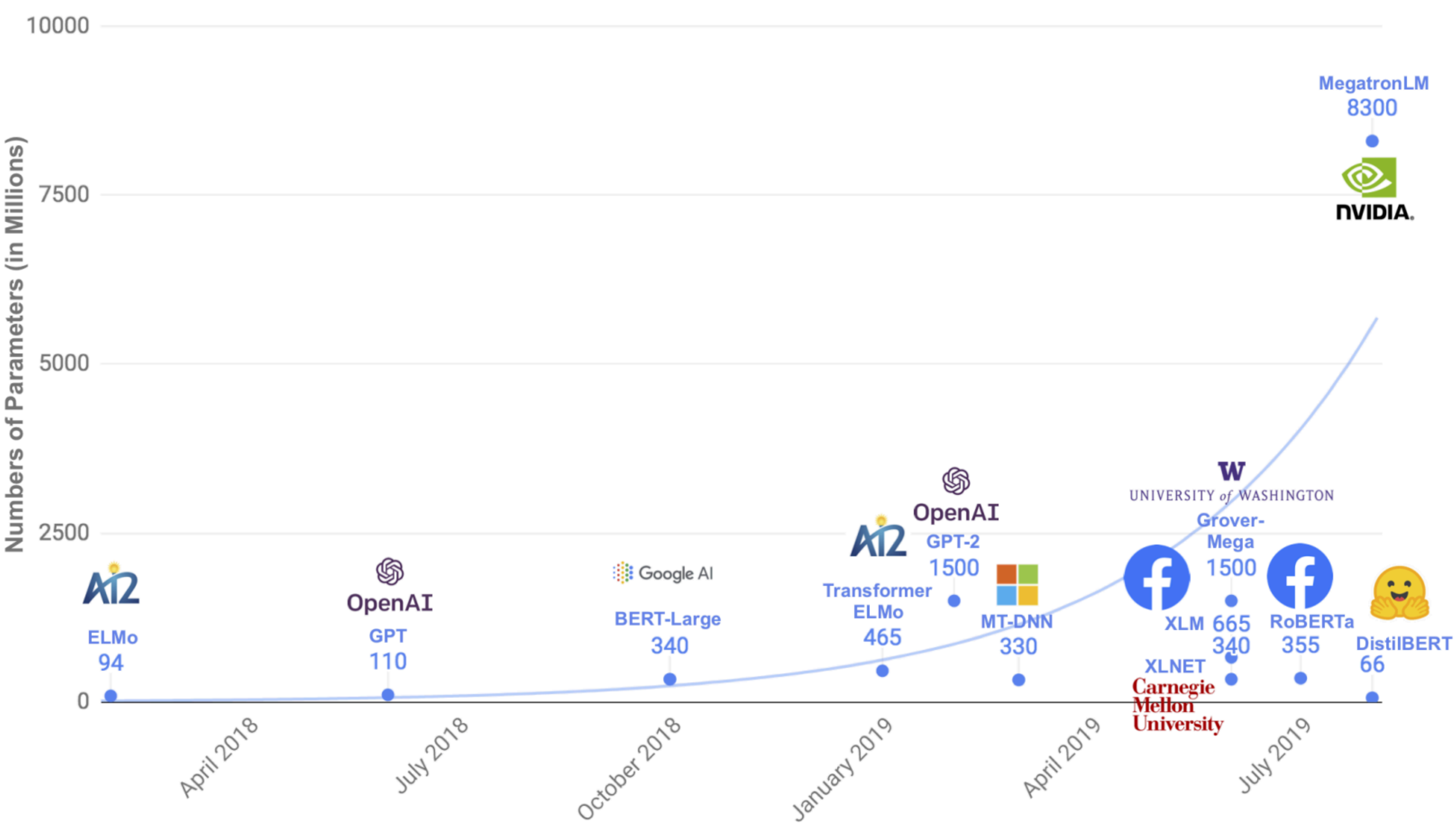
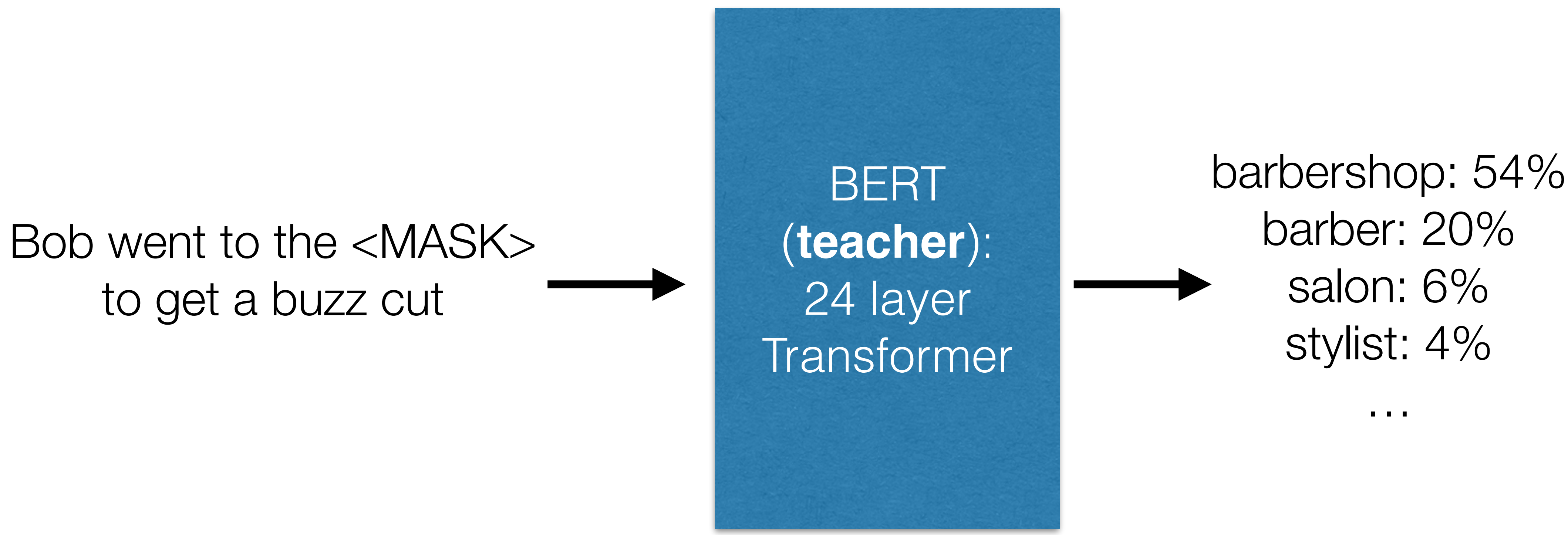
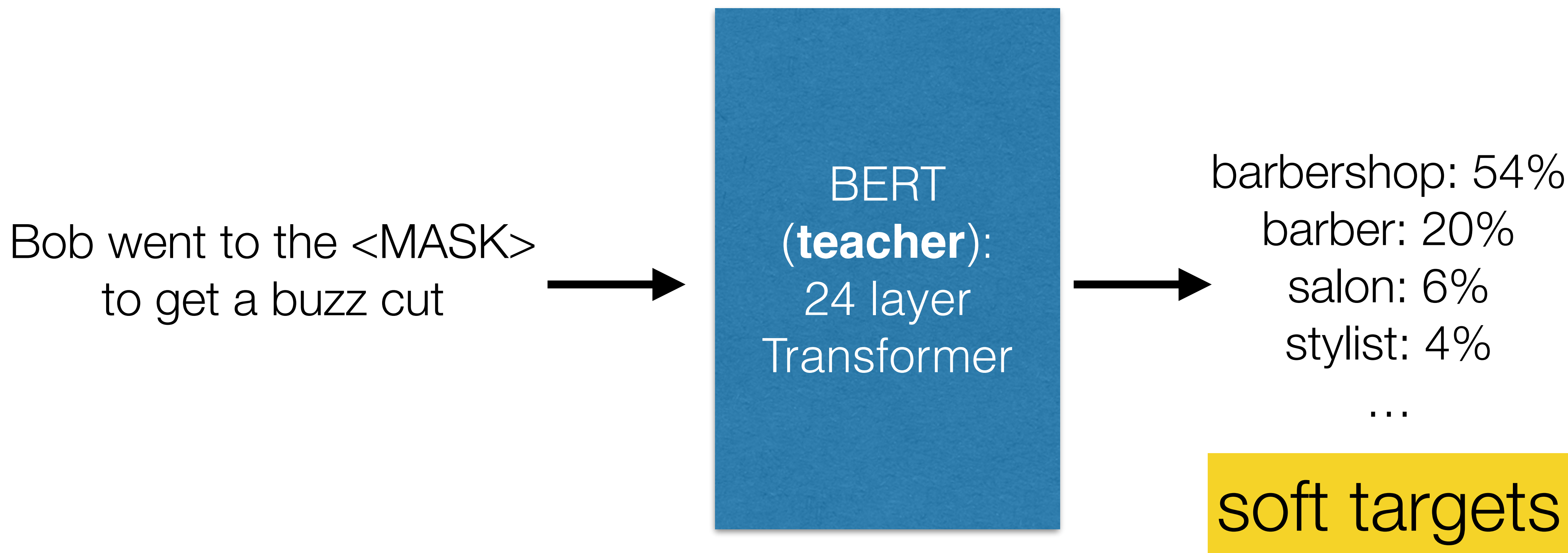


Figure 1: **Parameter counts of several recently released pretrained language models.**

Sanh et al., 2019 ("DistilBERT")


Bob went to the <MASK> to get a buzz cut
BERT (**teacher**): 24 layer Transformer
barbershop: 54%
barber: 20%
salon: 6%
stylist: 4%
...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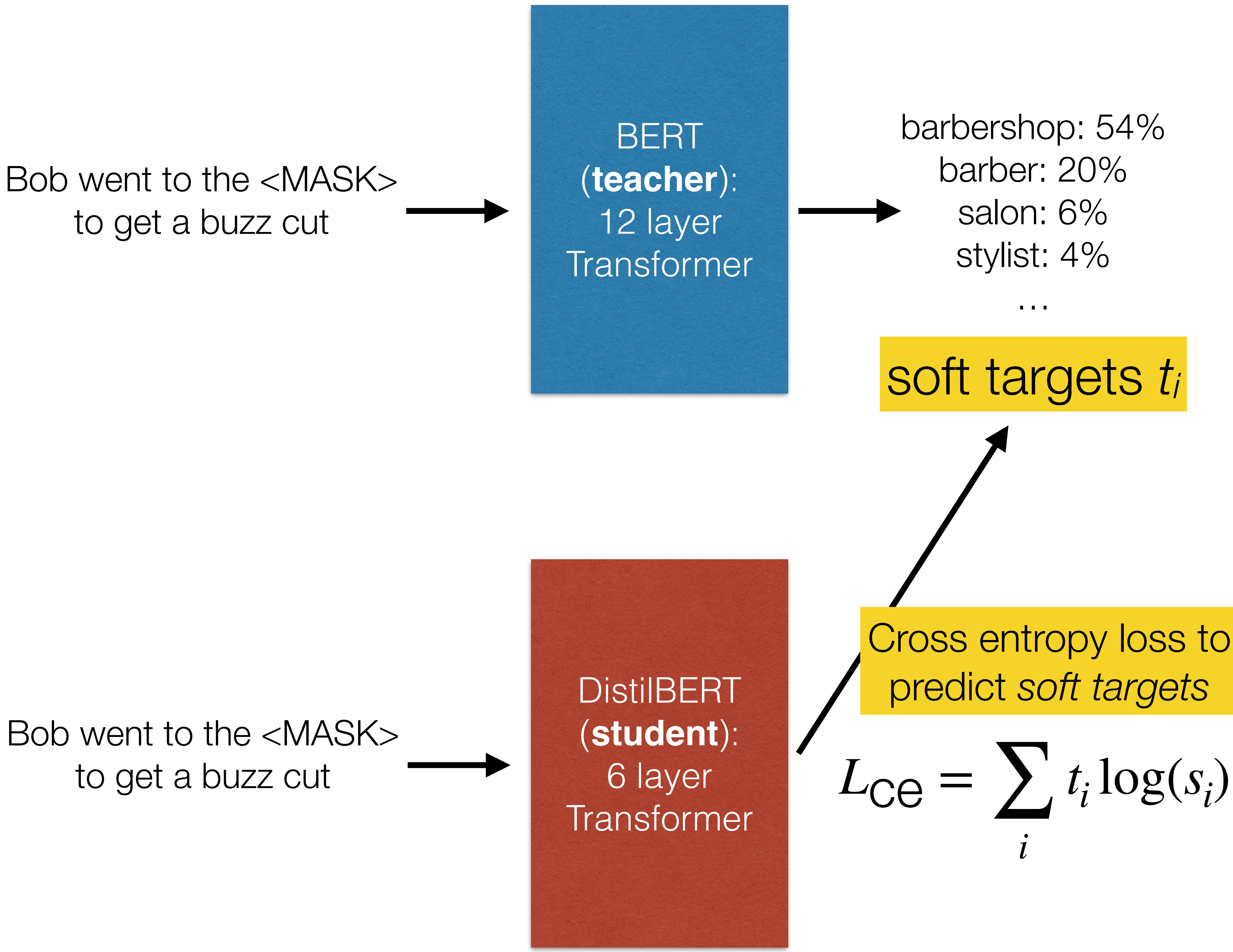
...
soft targets


Bob went to the <MASK> to get a buzz cut
BERT (**teacher**): 12 layer Transformer
barbershop: 54%
barber: 20%
salon: 6%
stylist: 4%
...
soft targets t_i
Bob went to the <MASK> to get a buzz cut
DistilBERT (**student**): 6 layer Transformer
Cross entropy loss to predict *soft targets*
$L_{ce} = \sum_i t_i \log(s_i)$

Instead of “one-hot” ground-truth, we have a full predicted distribution

- More information encoded in the target prediction than just the “correct” word
- Relative order of even low probability words (e.g., “church” vs “and” in the previous example) tells us some information
  - e.g., that the <MASK> is likely to be a noun and refer to a location, not a function word

Table 1: **DistilBERT retains 97% of BERT performance.** Comparison on the dev sets of the GLUE benchmark. ELMo results as reported by the authors. BERT and DistilBERT results are the medians of 5 runs with different seeds.

Model	**Score**	CoLA	MNLI	MRPC	QNLI	QQP	RTE	SST-2	STS-B	WNLI
ELMo	68.7	44.1	68.6	76.6	71.1	86.2	53.4	91.5	70.4	56.3
BERT-base	79.5	56.3	86.7	88.6	91.8	89.6	69.3	92.7	89.0	53.5
DistilBERT	77.0	51.3	82.2	87.5	89.2	88.5	59.9	91.3	86.9	56.3

Can also distill other parts of the teacher, not just its final predictions!

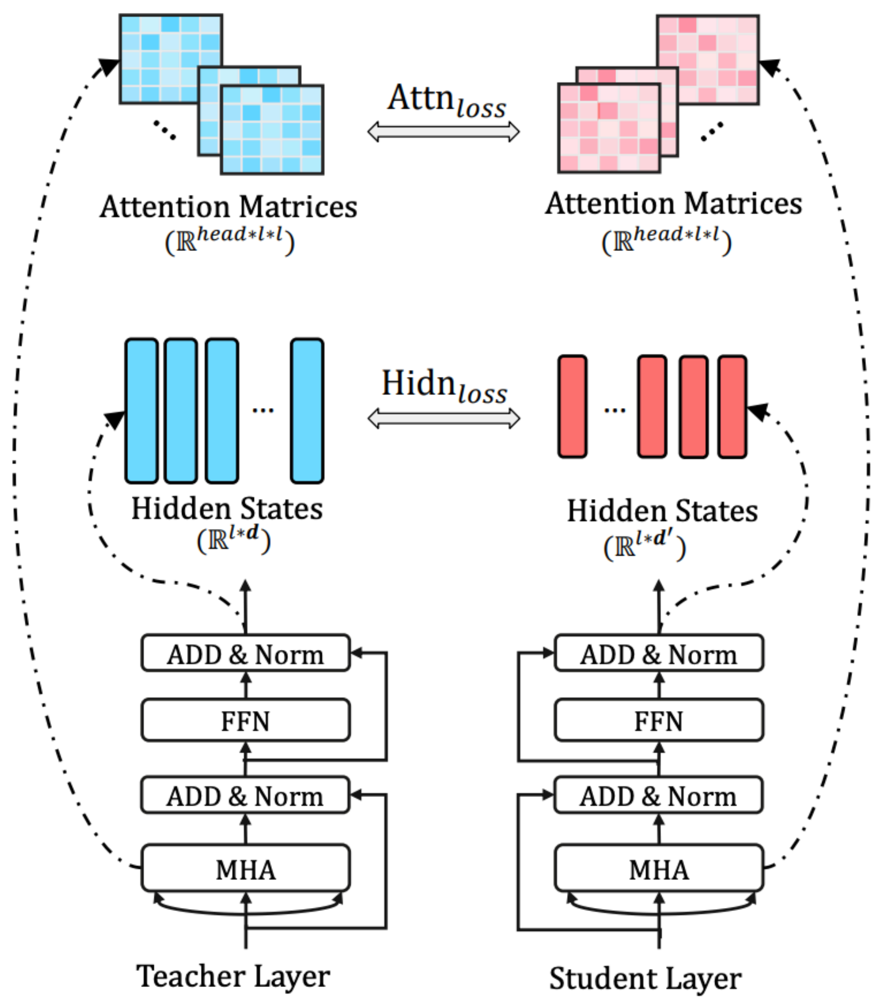
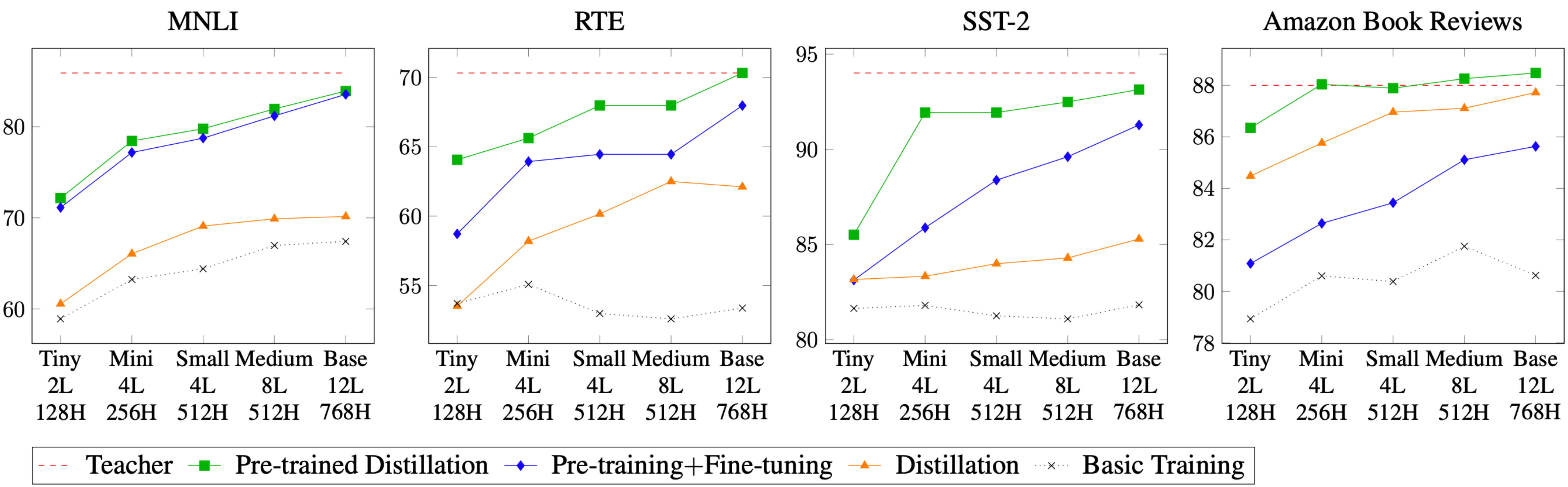


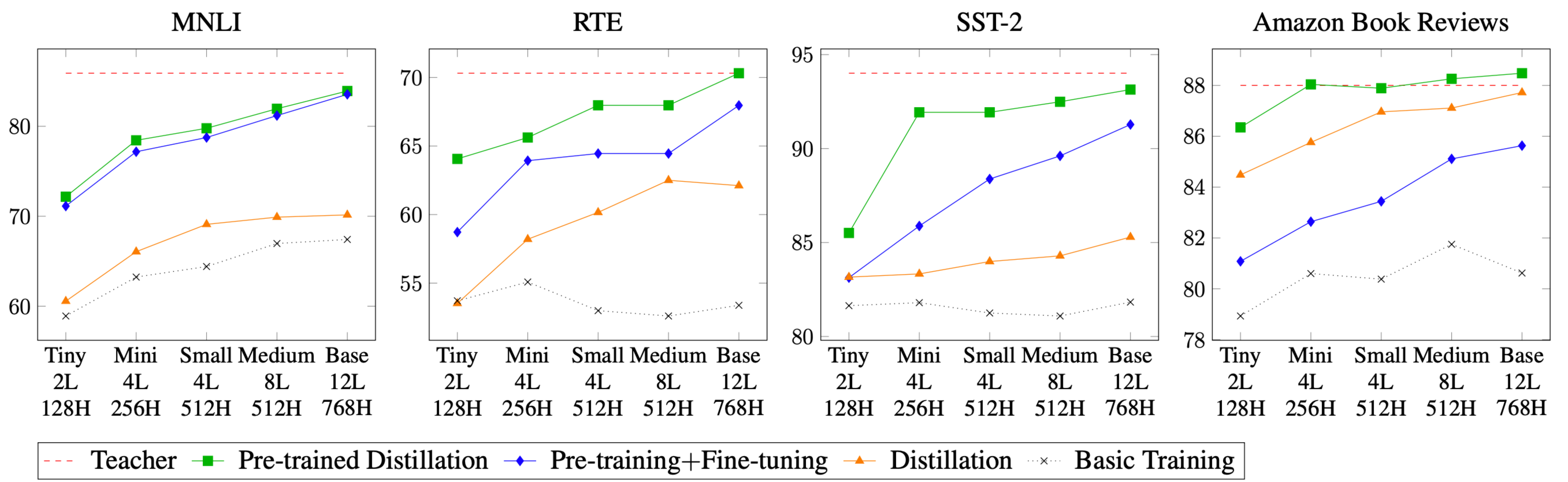
Figure 2: The details of Transformer-layer distillation consisting of Attn$_{loss}$(attention based distillation) and Hidn$_{loss}$(hidden states based distillation).

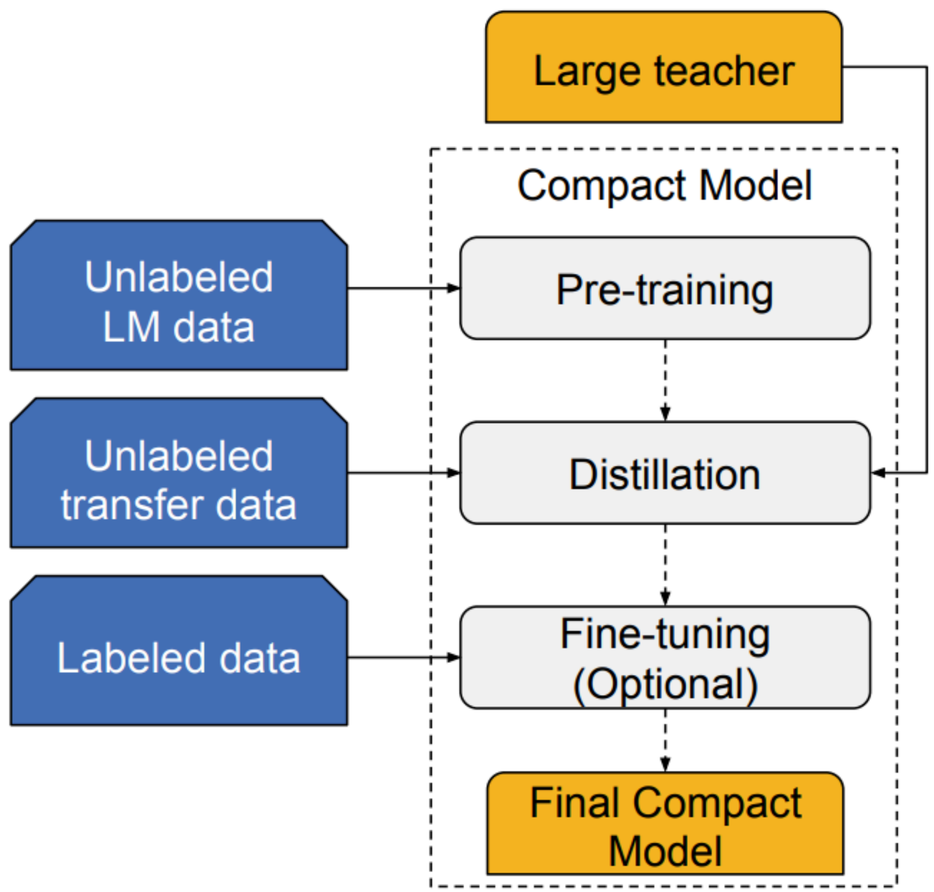
Jiao et al., 2020 ("TinyBERT")

Distillation helps significantly over just training the small model from scratch



Turc et al., 2019 (“Well-read students learn better”)





Turc et al., 2019 (“Well-read students learn better”)

The Lottery Ticket Hypothesis. *A randomly-initialized, dense neural network contains a subnetwork that is initialized such that—when trained in isolation—it can match the test accuracy of the original network after training for at most the same number of iterations.*

1. Randomly initialize a neural network $f(x; \theta_0)$ (where $\theta_0 \sim \mathcal{D}_\theta$).
2. Train the network for j iterations, arriving at parameters θ_j.
3. Prune $p\%$ of the parameters in θ_j, creating a mask m.
4. Reset the remaining parameters to their values in θ_0, creating the winning ticket $f(x; m \odot \theta_0)$.

How to prune? Simply remove the weights with the lowest magnitudes in each layer

Frankle & Carbin, 2019 (“The Lottery Ticket Hypothesis”)

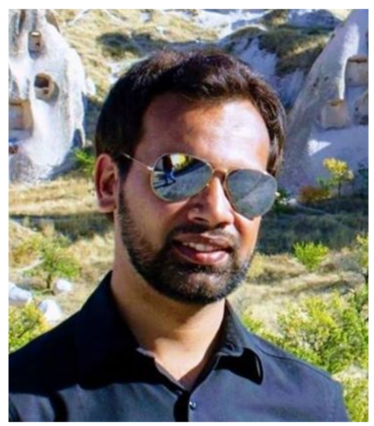
Can prune a significant fraction of the network with no downstream performance loss

Dataset	MNLI	QQP	STS-B	WNLI	QNLI	MRPC	RTE	SST-2	CoLA	SQuAD	MLM
Sparsity	70%	90%	50%	90%	70%	50%	60%	60%	50%	40%	70%
Full $\text{BERT}_{\text{BASE}}$	82.4 ± 0.5	90.2 ± 0.5	88.4 ± 0.3	54.9 ± 1.2	89.1 ± 1.0	85.2 ± 0.1	66.2 ± 3.6	92.1 ± 0.1	54.5 ± 0.4	88.1 ± 0.6	63.5 ± 0.1
$f(x, m_{\text{IMP}} \odot \theta_0)$	82.6 ± 0.2	90.0 ± 0.2	88.2 ± 0.2	54.9 ± 1.2	88.9 ± 0.4	84.9 ± 0.4	66.0 ± 2.4	91.9 ± 0.5	53.8 ± 0.9	87.7 ± 0.5	63.2 ± 0.3
$f(x, m_{\text{RP}} \odot \theta_0)$	67.5	76.3	21.0	53.5	61.9	69.6	56.0	83.1	9.6	31.8	32.3

Chen et al., 2020 (“Lottery Ticket for BERT Networks”)

What if you only have access to the model's argmax prediction, and you also don't have access to its training data?

Thieves on Sesame Street!
Model Extraction of BERT-based APIs


Kalpesh Krishna[1]
Gaurav S. Tomar[2]
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Nicolas Papernot[2]
Mohit Iyyer[1]

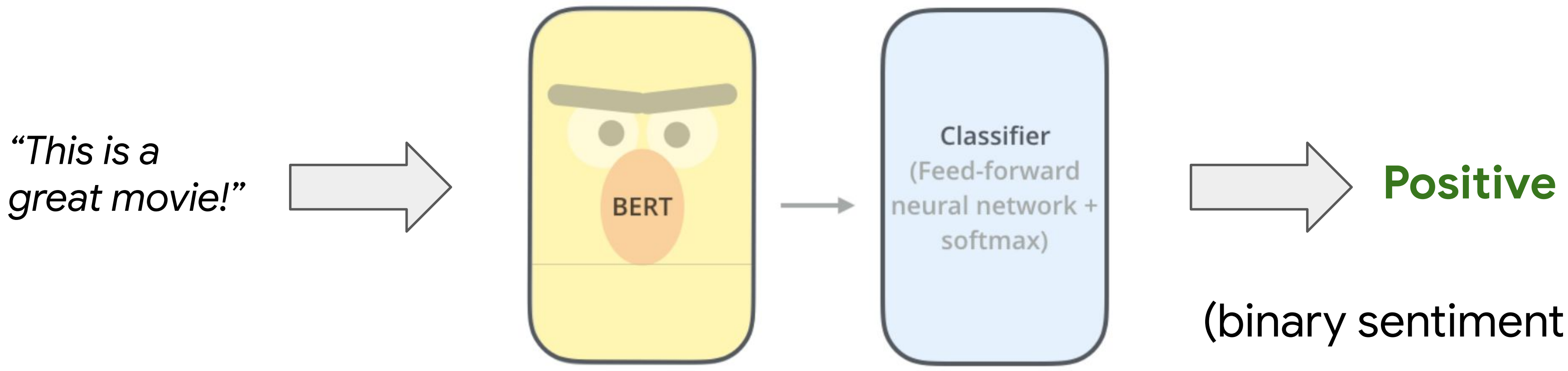
1 UMass Amherst

2 Google AI

Work done during an internship at Google AI Language.

What are model extraction attacks?

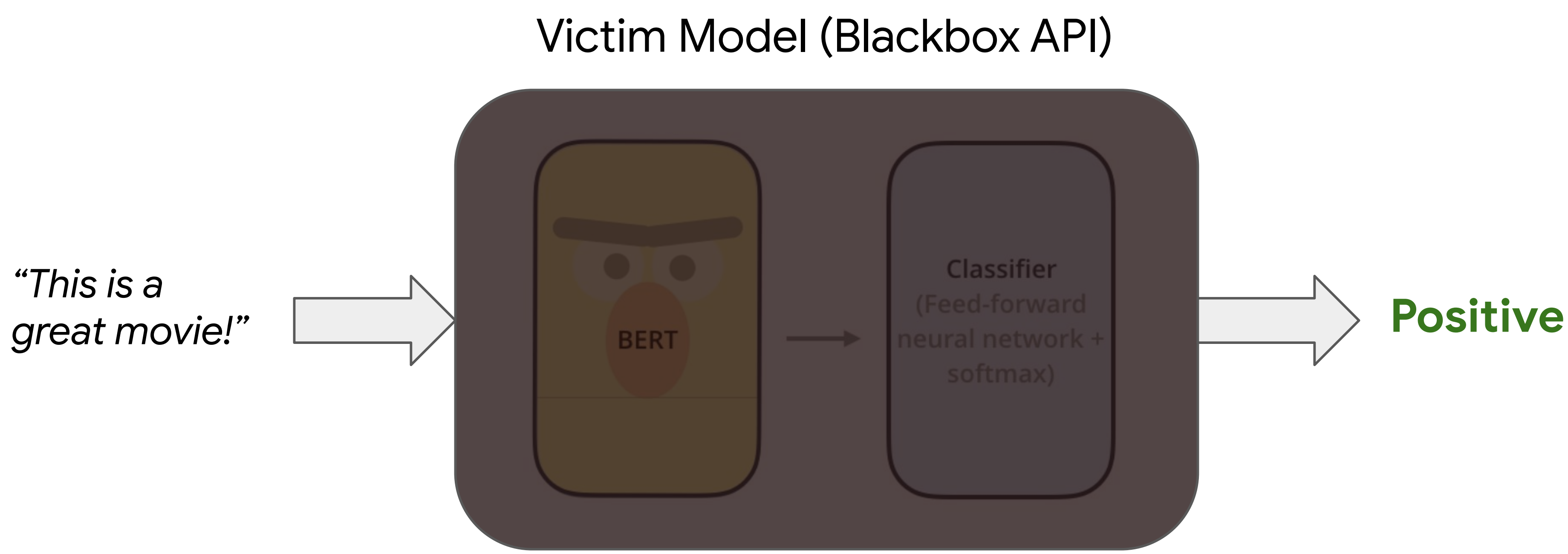
Victim Model (Blackbox API)



(binary sentiment classification)

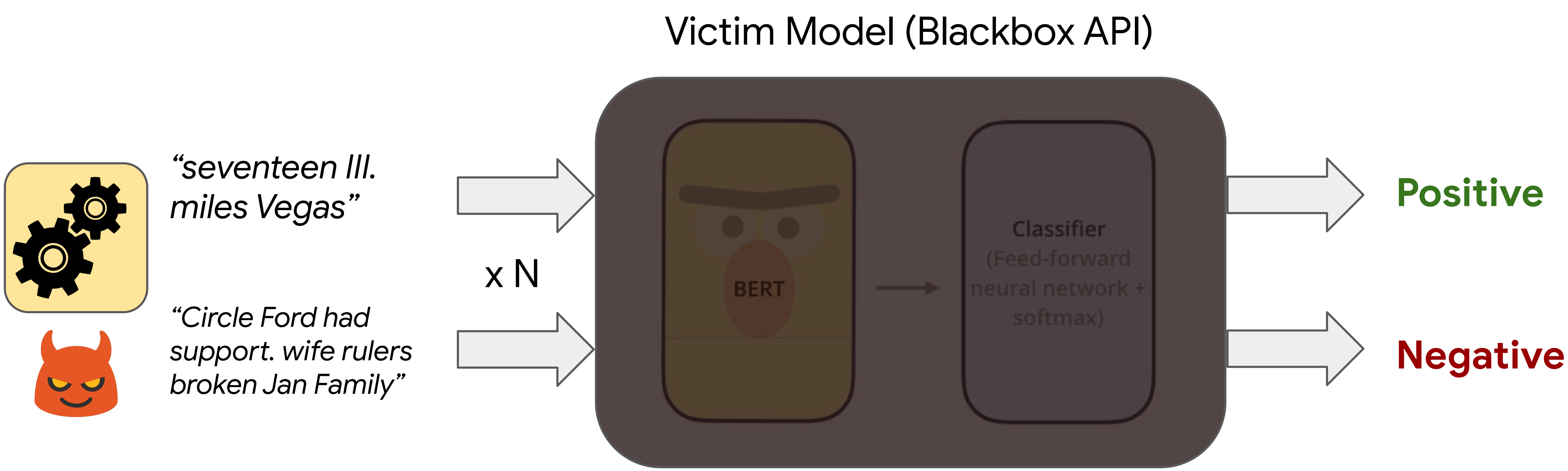
A company trains a binary sentiment classifier based on BERT

Photo credits - http://jalammar.github.io/illustrated-bert/

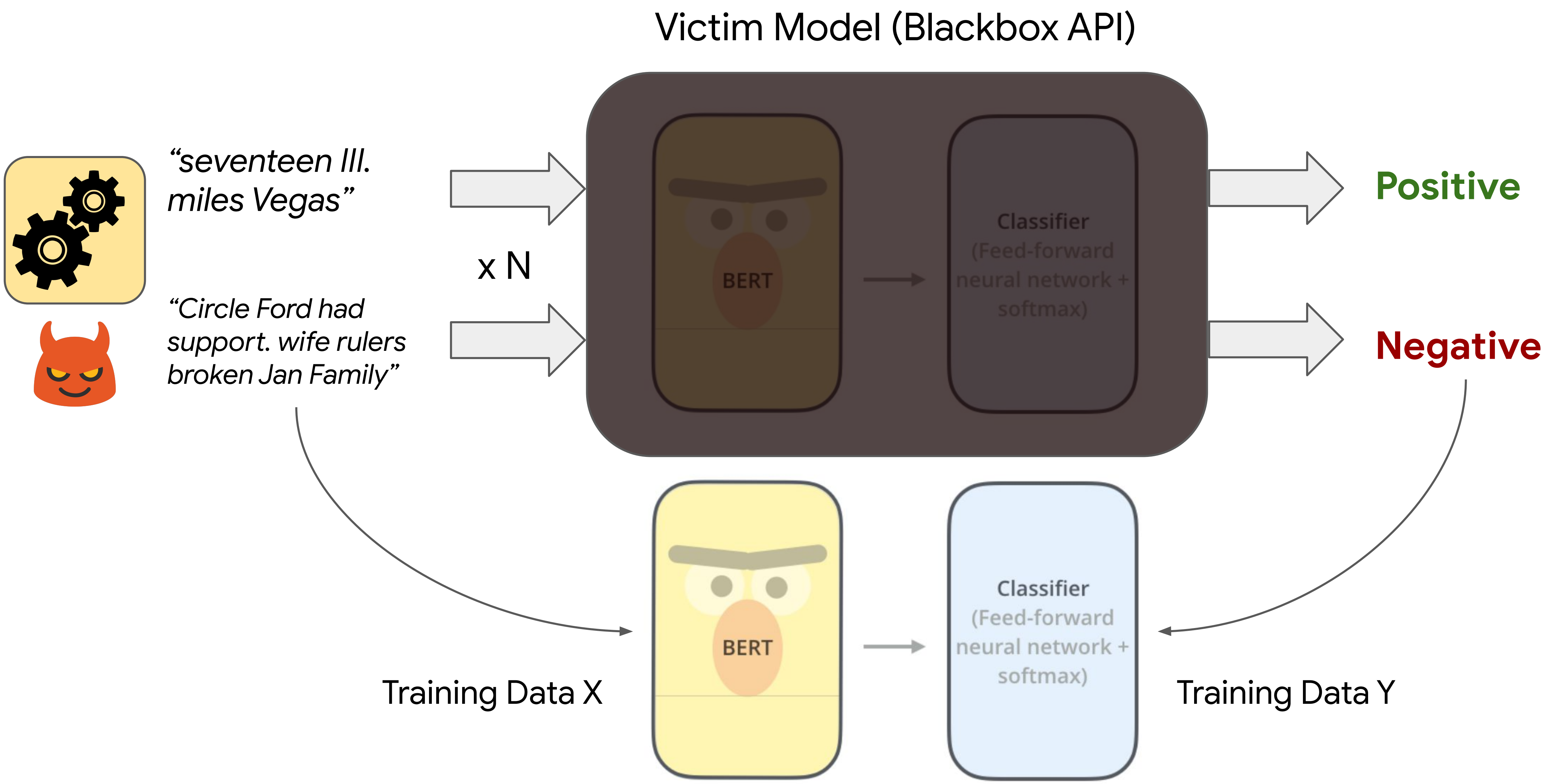


It is released as a black-box API (the “victim model”)

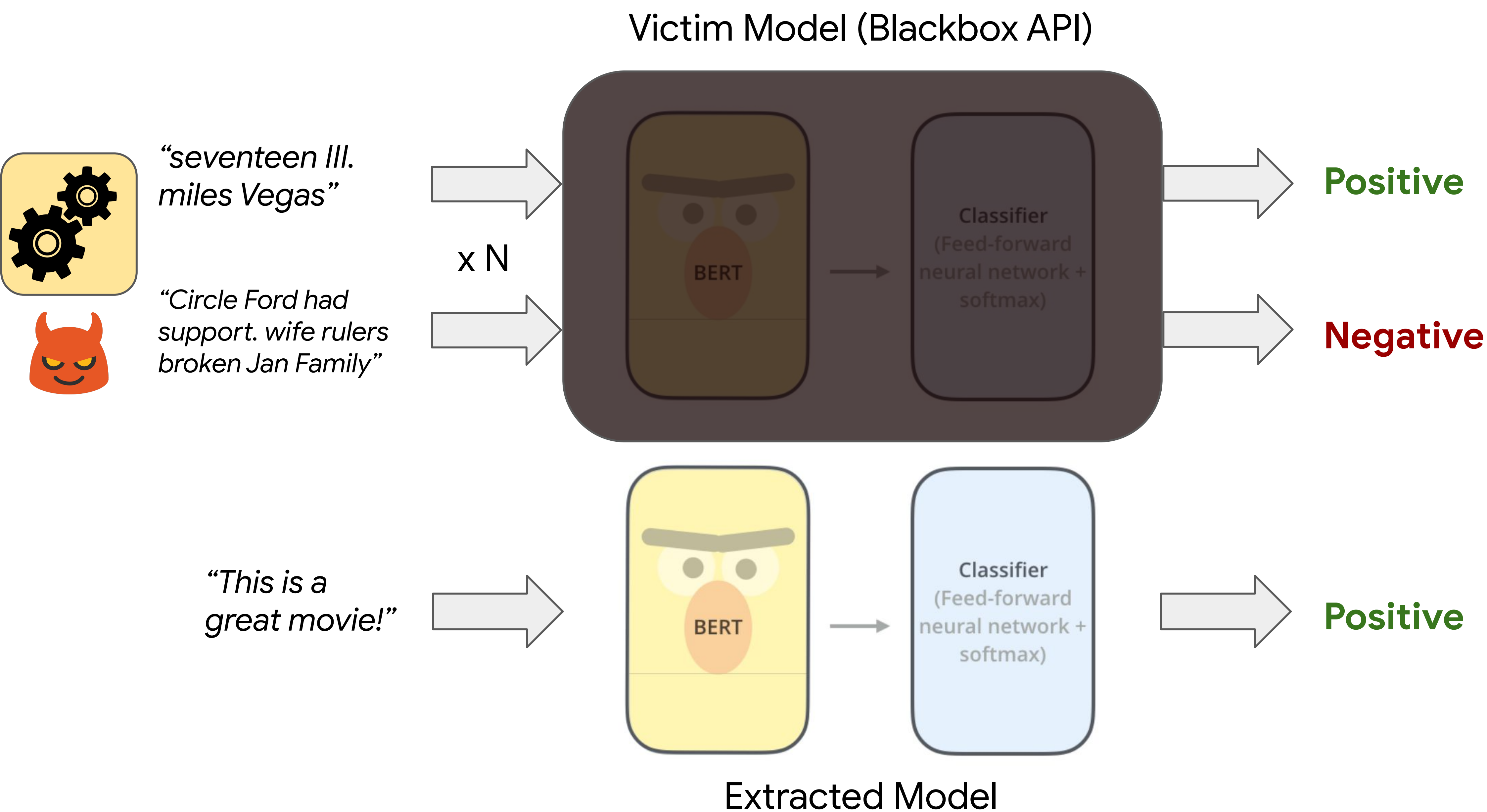
A malicious user generates many queries
(in this work, **random gibberish sequences of words**)



The attacker queries the API with the generated inputs and collects the labels



The collected data is used to train a “copy” of the model

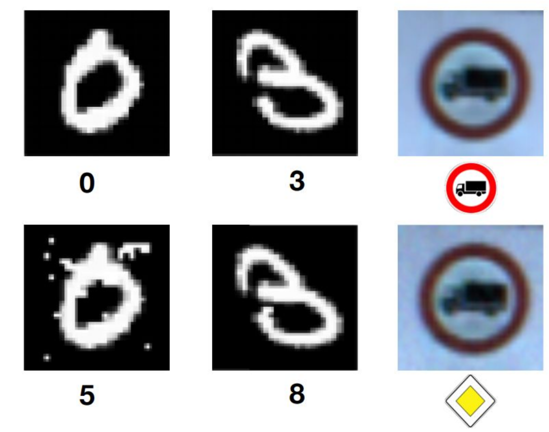


The stolen copy (“extracted model”) works well on real data

Why is model extraction a problem?

Theft of intellectual property

Leakage of original training data



Adversarial example generation

Image credits - [Papernot et al. 2017](), [Fredrikson et al. 2015]()

These attacks are economically practical

Google Cloud Natural Language API cost <= $1.00 per 1000 API calls.

Dataset	**Size**	**Upperbound Price**
SST2 (sentiment classify)	67349 sentences	$62.35
Switchboard (speech)	300 hours	$430.56
Translation	1 million sentences (100 characters each)	$2000.00

Smart attackers can scrape APIs like Google Translate for free

https://cloud.google.com/products/calculator/

How is this different from distillation?

No training data

Goal is theft, not compression

We attack BERT models for,

1) sentiment classification (SST2)
2) natural language inference (MNLI)
3) question answering (SQuAD, BoolQ)

We use two query generators - RANDOM & WIKI

RANDOM
(gibberish sequences of words sampled from a fixed vocabulary)

1. cent 1977, preparation (120 remote Program finance add broader protection
2. Mike zone fights Woods Second State known, defined come

WIKI
(sentences from Wikipedia)

1. The unique glass chapel made public and press viewing of the wedding easy.
2. Wrapped in Red was first released internationally on October 25, 2013.

For multi-input tasks (like question answering) we ensure inputs are related to each other

RANDOM Paragraph: as and conditions Toxostoma storm, The interpreted. Glowworm separation Leading killed Papps wall upcoming Michael Highway that of on other Engine On to Washington Kazim of consisted the ” further and into touchdown(AADT), Territory fourth of h; advocacy its Jade woman ”lit that spin. Orange the EP season her General of the

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RANDOM Question: Kazim Kazim further as and Glowworm upcoming interpreted. its spin. Michael as

Results - attacks are effective

	# of Queries	SST2 (%)	MNLI (%)	SQUAD (F1)
API / Victim Model	1x	93.1	85.8	$\boxed{90.6}$
RANDOM	1x	90.1	76.3	79.1
RANDOM	upto 10x	90.5	78.5	85.8
WIKI	1x	91.4	77.8	86.1
WIKI	upto 10x	91.7	79.3	89.4

A BERT model trained on the real SQuAD data gets 90.6 F1

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RANDOM achieves 85.8 F1 (**~95%** performance) **without seeing a single grammatically valid paragraph or question** during training

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WIKI achieves 89.4 F1 (**~99%** performance) without seeing a single grammatically valid question during training

Key findings from experimental analysis

- better pretraining ⇒ better model extraction

- WIKI / RANDOM queries closer to the victim model's learnt distribution are more effective

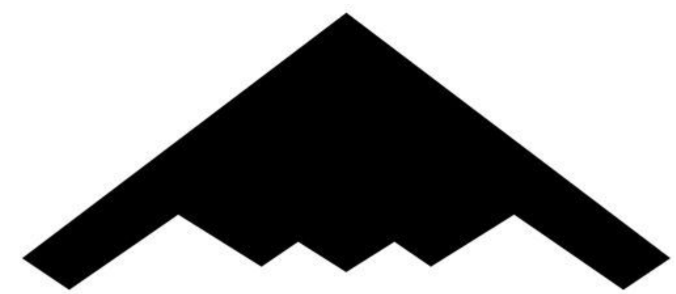
What is a good defense?

Stops or delays model extraction

~~Accuracy = 91.2%~~

Accuracy = 91.1%

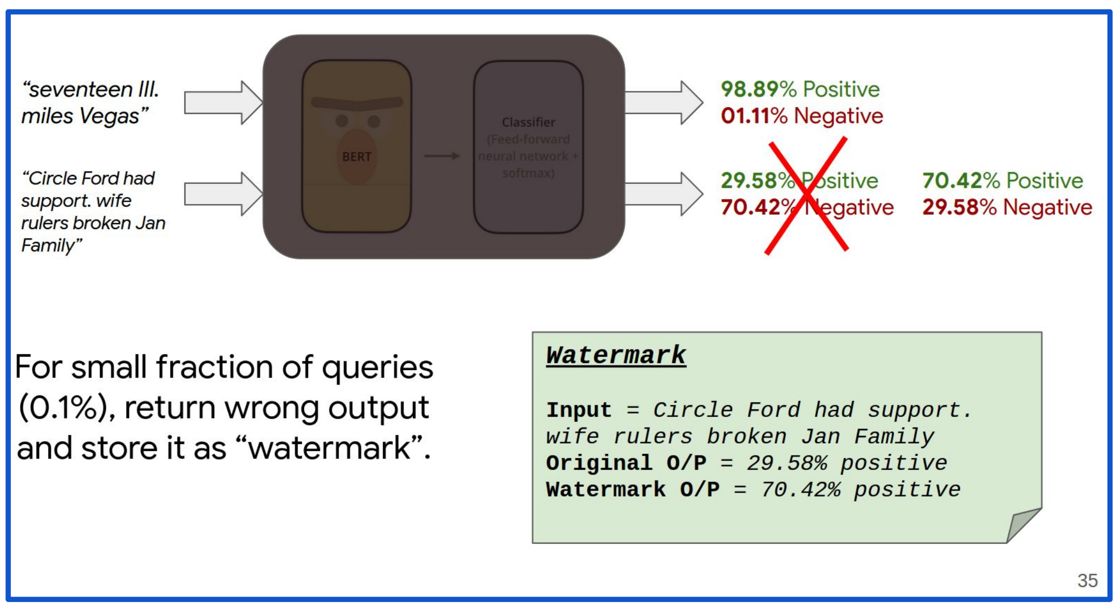
Utility preserving



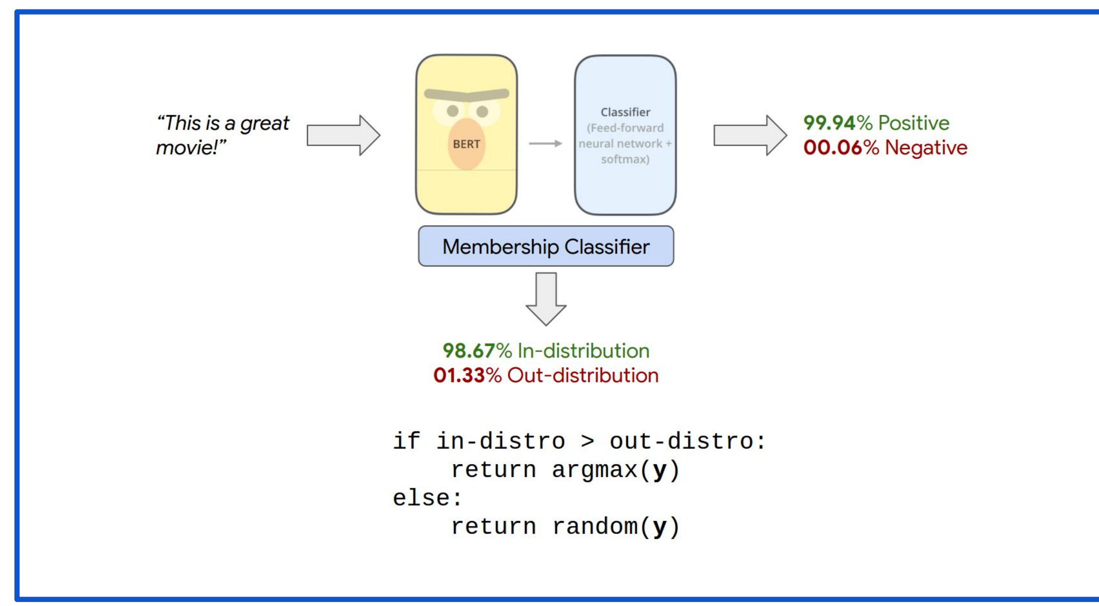
Stealthy, to prevent counter-attacks

What defenses do we investigate in the paper?

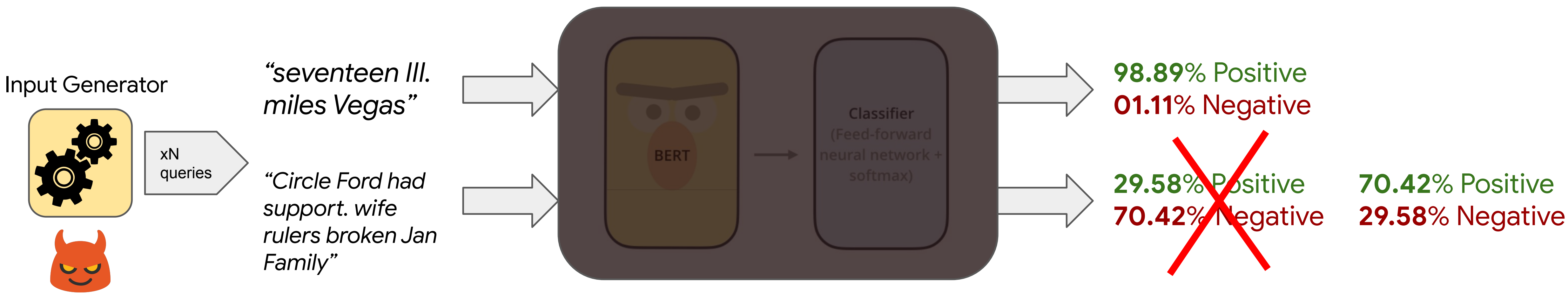
API Watermarking



Membership Classification



What is watermarking?



For small fraction of queries (0.1%), return wrong output and store it as "watermark".

Watermark

Input = *Circle Ford had support. wife rulers broken Jan Family*
Original O/P = *29.58% positive*
Watermark O/P = *70.42% positive*

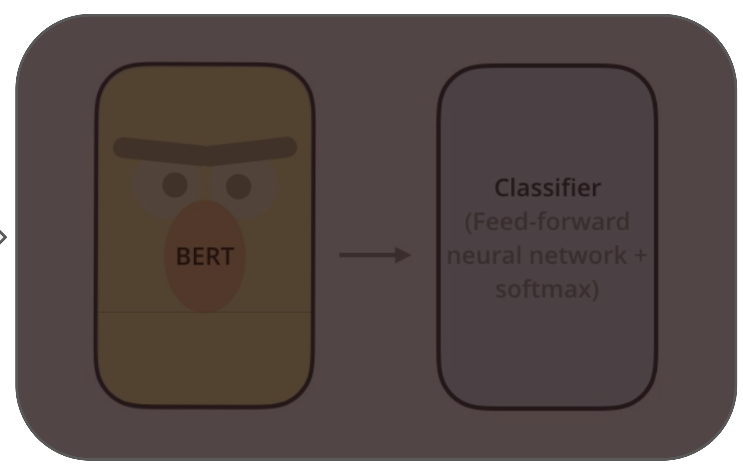
Watermark verification

Watermark

Input = *Circle Ford had support.*
wife rulers broken Jan Family
Original O/P = *29.58% positive*
Watermark O/P = *70.42% positive*

Verify watermark if stolen model is released with query access.

"Circle Ford had support. wife rulers broken Jan Family"



65.42% Positive
34.58% Negative

Stolen Model

Deep models have high capacity!

Extracted model will memorize watermarks

Watermarking works well!

Task	Model	Watermark w/ Wrong Labels	Watermark w/ Correct Labels
MNLI	WIKI	2.8%	94.4%
MNLI	watermarked WIKI	52.8%	35.4%
MNLI	watermarked WIKI (10 epochs)	87.2%	7.9%
SQUAD	WIKI	0.0 EM	94.3 EM
SQUAD	watermarked WIKI	5.7 EM	14.9 EM
SQUAD	watermarked WIKI (10 epochs)	74.7 EM	1.1 EM

No significant change in dev accuracy!

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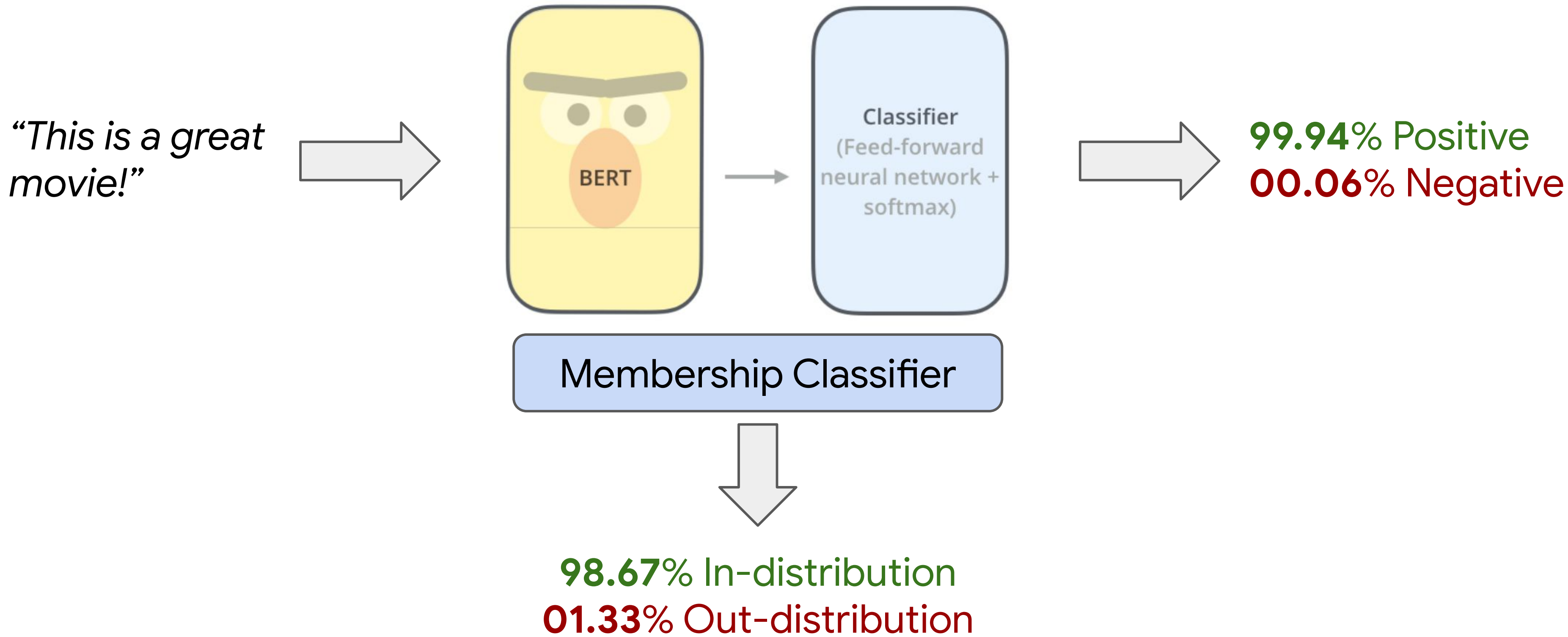
Limitation #1

watermarking requires public access to extracted model

Limitation #2

counter-attack with differentially private training / double extraction possible

What is membership classification?




```
if in-distro > out-distro:
    return argmax(y)
else:
    return random(y)
```

Membership Classification

- Train binary classifier with features last layer + logits of trained API
- classify training data vs WIKI attack data
- Evaluate on dev set + auxiliary test sets

Task	Features	WIKI %	RANDOM %	SHUFFLE %
MNLI	last layer + logits	99.34%	99.14%	87.36%
	logits	90.66%	91.20%	82.34%
	last layer	99.15%	99.05%	88.88%
SQuAD	last layer + logits	98.78%	99.97%	99.70%
	logits	81.45%	84.72%	81.99%
	last layer	98.79%	98.89%	98.97%

Limitation:
Genuine queries can be out-of-distribution
but still sensible

Only works for **RANDOM** queries